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Simple-Offer vs. Complex-Offer Auctions in Deregulated Electricity Markets

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Abstract

In my recent experimental research of wholesale electricity auctions, I discovered that the complex structure of the offers leaves a lot of room for strategic behavior, which consequently leads to anti- competitive and inefficient outcomes in the market. A specific feature of these complex-offer auctions is that the sellers submit not only the quantities and the minimum prices at which they are willing to sell, but also the start-up fees that are designed to reimburse the fixed start-up costs of the generation plants. In this paper, using the experimental method I compare the performance of two complex-offer auctions (COAs) against the performance of a simple-offer auction (SOA), in which the sellers have to recover all their generation costs — fixed and variable —through a uniform market-clearing price. I find that the SOA significantly reduces consumer prices and lowers price volatility. It mitigates anti-competitive effects that are present in the COAs and achieves allocative efficiency more quickly.

Journal of Economic Literature Classification: C72, D4, D61, L94

Keywords: strategic behavior, sealed-bid auction, complex offer auction, electricity, efficiency

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1. Introduction

Many wholesale electric power markets employ auctions that differ from other widely used quantity-price offer auctions in their offer complexity. Besides the quantities and the minimum prices that the electricity generators are willing to sell at, the sellers may also declare their technical constraints and start-up fees that are designed to reimburse the fixed start-up costs of the plants. The generation contracts are generally allocated by a sealed-offer auction that employs a computationally involved market-clearing algorithm. Besides applying a rule for offer selection, a market-clearing algorithm has to ensure that the system demand and reserve requirements are met over a particular time period. Recently, I compared the performance of two such algorithms by using laboratory experiments (Baltaduonis 2007). The major finding is that the sellers exploit the offer complexity to extract higher payments from the buyers. Consequently, the resulting outcomes are substantially inefficient. In this paper, I use laboratory experiments to contrast the performance of these complex-offer auctions (COAs) against the performance of a simple-offer auction (SOA). In the SOA, the sellers can recover their generation costs – both fixed and variable – only through a uniform market-clearing price. The paper investigates whether the SOA could mitigate the anti-competitive behavior present in the COAs.

Two complex-offer auctions that I discuss in this paper differ from each other in their market-clearing algorithms. An offer cost minimization (OCM) algorithm is currently used by independent system operators (ISOs) in the United States. It relies on the traditional unit commitment approach.[2] The algorithm minimizes the total offered cost of electricity, as if all selected sellers would be paid their offered prices and fees.

[2] For a bibliographical survey on the unit commitment problem see Padhy (2004).

Sequentially, after the offers are selected, a uniform market-clearing price is determined as the highest accepted price for that period. All selected sellers receive their individual start-up fees and the uniform market-clearing price for the supplied electricity during that period.

Yan and Stern (2002) point out that the OCM algorithm does not ensure the lowest procurement cost of electricity to consumers for a given set of offers. This motivated Luh et al. (2005a) to develop a payment cost minimization (PCM) algorithm that minimizes the actual procurement cost of electricity, *simultaneously* determining a market-clearing price as the highest accepted price during that period. As in the OCM auction, the selected sellers would receive their individual start-up fees and the uniform market-clearing price for the supplied electricity.

Mixed integer programming problems, similar to the OCM and the PCM algorithms, have been actively studied in electrical engineering for several decades because of potential savings in generation costs. The improvement of these mechanisms heavily depended on the assumption of complete information about the generation costs of electricity. Even if such an assumption might be practical in a regulated or state-owned electricity system, there is no guarantee that complete information would be available to an ISO in a deregulated electricity market. One might hope that competitive forces in the market would induce the sellers to reveal their true generation costs. If so, the ISOs could continue to use the developed allocation programs. Unfortunately, this seems to be unlikely in the case of complex-offer auctions. Baltaduonis (2007) shows that in both the OCM and the PCM auctions, sellers significantly raise the start-up fees and prices over their true start-up costs and variable generation costs even in a competitive environment. Such behavior leads to both allocative and production inefficiencies.

This paper investigates the performance of a SOA, holding constant all other characteristics of the system described by Baltaduonis (2007). The SOA is a less computationally involved auction than the COAs. On the other hand, the exact revelation of electricity generation costs is impossible in the SOA. The sellers have to mark up their offered prices to account for the fixed start-up costs or they might incur losses. If the study shows that the complex-offer auctions do provide value-added, it could help to improve market mechanisms for industries where the fixed cost component is an important production characteristic.

There are other studies of strategic behavior by sellers in the complex-offer auctions used in wholesale electricity markets. Knoblauch (2005) points out that if suppliers tailor their offers to the type of auction they face, it is no longer obvious that the PCM auction will generate lower procurement costs. Shunda (2005) extends Knoblauch's analysis by including strategic capacity withholding behavior between day-ahead and real-time markets for electricity. Baltaduonis (2006) uses a game theoretic approach to analyze the performance of the OCM and the PCM auctions with regards to efficiency. This paper, to my knowledge, is the first experimental study that contrasts simple- and complex-offer auctions in the context of electricity markets. As in Rassenti, Smith & Wilson (2003a, 2003b), hereafter RSW, the analysis allows for strategic behavior, strictly controls for the level of unilateral market power, and simulates trading environments with minimal demand elasticity, cyclical demand uncertainties and an absence of significant excess generation capacity.

The paper is organized as follows. *Market Institution, Structure, and Environment* outlines the market structure in the experiment and provides an example that highlights the major differences among the three auctions. This section describes market power in a sealed COA. *Experimental Design and Procedures* describes the design and procedures of the experiment, and *Results* presents the findings. *Conclusions* summarizes and discusses the implications for public policy.

2. Market Institution, Structure, and Environment

To isolate the institutional effects of the strategically complex auctions, I examine a very simple environment, relative to actual electric power systems: (i) transmission constraints are negligible; (ii) generators have no physical ramping rates; (iii) security reserves and other ancillary services to protect the system from outages are ignored; and (iv) a trading institution accepts flat offer curves for each generating unit. Such an environment is most comparable to the day-ahead wholesale markets of observed power systems. Hour-ahead and real-time power markets are organized in a similar fashion. The performance of the SOA is measured against the OCM and the PCM auctions in a stationary supply and cyclic demand environment, strictly controlling for unilateral market power.

2.1. Auction Institution

The objective of this paper is to compare the performance of a SOA versus two COA rules (OCM and PCM), while holding constant all other characteristics of the system – the costs and structure of supply, the resale values and structure of demand. The criteria for evaluation are consumer prices, efficiency and price volatility. Since demand-side bidding is often absent in the naturally occurring spot markets for electricity, a computer is used to submit bids that perfectly reveal the demand at any point in time in all experiments, as in RSW. The sellers privately submit a schedule of offers, i.e. plant start-up fees and prices, for their production capacity for each pricing period. The offers and the computerized bids are then sent to a market-clearing algorithm to allocate the production contracts for the next day. Each day consists of four pricing periods: night (low demand/off peak period), morning (medium demand/shoulder period), afternoon (high demand/peak period) and evening (medium demand/shoulder period). Four pricing periods during the day are a simplification of the naturally occurring day-ahead electricity markets where separate prices are instituted hourly. Nevertheless, the cyclical dynamics of the demand are preserved.

Currently, the dominant practice in the electricity spot markets is to employ uniform price auctions, where each seller receives the same market price for the sold megawatts. The market price is usually the highest accepted price per megawatt among all of the sellers. I retain these institutional features and leave aside the discussion of "pay-as-offered" discriminatory price auctions.[3] In all experimental treatments, i.e. OCM, PCM and SOA, the sellers are paid uniform prices and their individual start-up fees. Note that in the SOA, the start-up fees are simply constrained to be zero.

In the case of a uniform-price auction where sellers ask for fixed start-up fees, the mechanism of distributing these fees across consumers is important. One way to do that

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[3] For experimental investigations of uniform price versus discriminatory price auctions with simple offers see Mount, Schulze, Thomas & Zimmerman (2001), and Rassenti, Smith & Wilson (2003b).

is to divide the borne fees equally over the units dispatched during the period for which the extra generation capacity was called. The markup on offered price creates a gap between a uniform price that all sellers receive and a uniform price that all buyers pay. In this experiment, both the OCM and the PCM algorithms employ this method to compute the buyer prices and to determine the corresponding levels of demand. Note that a uniform price that all sellers receive and a uniform price that all buyers pay are the same in the SOA due to the absence of start-up fees.

The following numerical example demonstrates the principles of the offer-selection rules for all three auctions.

Example: A Simple Wholesale Electricity Market

To highlight the major differences in the preceding market-clearing rules, I use a three-supplier market described by Knoblauch (2005). Consider an electricity market for one hour. The demand is inelastic and equal to 2 units. Supplier 1 (*S*1) and Supplier 2 (*S*2) are identical. They incur 6 dollars of fixed costs to start up their plants and 93 dollars of variable costs to generate one unit of electricity. Each of them can supply 0, 1 or 2 units of energy. Supplier 3 (*S*3) has start-up cost of 20 dollars and energy cost of 70 dollars per unit. She can supply 0 or 1 unit of energy.

For the purpose of this example suppose that all suppliers submit offers that reflect their true production costs. Since the fees are constrained to be zero in the SOA, the suppliers would incur losses unless they recover their fixed costs through the prices. Therefore, in the SOA, the fixed cost can be evenly distributed over the energy cost at the full capacity level of a plant. In this case, *S*1 and *S*2 would submit offers of 96 (=93+6÷2) dollars per unit and *S*3 would submit an offer of 90 (=70+20) dollars per unit. Given these offers the three auctions would generate the following outcomes.

The OCM Auction

The OCM algorithm minimizes the total offered cost of electricity, as if all selected sellers would be paid their offered prices and fees. Given the offers, an ISO calculates the minimum offered cost from two cases: 1) buying 2 units from either *S*1 or *S*2, OR 2) buying 1 unit from *S*3 and 1 unit from *S*1(*S*2):

$$\text{Min}\{Price_{1,2}\times 2+Fee_{1,2}\ ,\ Price_3+Fee_3+Price_{1,2}+Fee_{1,2}\},$$

$$\text{Min}\{93\times 2+6,\ 70+20+93+6\}=70+20+93+6=189.$$

The auction chooses to buy 1 unit from *S*3 and 1 unit from *S*1(*S*2). After the offers are selected, a uniform market-clearing price is determined as the highest accepted price for that period; the market price is 93 (=max{70, 93}). All selected sellers receive their individual start-up fees and the uniform market price for the supplied electricity during that period; the total procurement cost of electricity is 212 (=93×2+20+6). The uniform market price that all buyers pay is 106 [=93+(20+6)÷2)]. Notice that this contract allocation is production efficient, since there is no way to generate 2 units of electricity cheaper than the chosen suppliers do.

The PCM Auction

The PCM algorithm minimizes the actual procurement cost of electricity, simultaneously determining a market-clearing price as the highest accepted price during that period. An ISO calculates the minimum procurement cost in two cases: 1) buying 2 units from either *S*1 or *S*2, OR 2) buying 1 unit from *S*3 and 1 unit from *S*1(*S*2):

$$\mathrm{Min}\{Price_{1,2}\times 2+Fee_{1,2}\ ,\ \max\{Price_3\ ,\ Price_{1,2}\}\times 2+Fee_3+Fee_{1,2}\},$$

$$\mathrm{Min}\{93\times 2+6,\ \max\{70,\ 93\}\times 2+20+6\}=93\times 2+6=192.$$

The auction chooses to buy 2 units from *S*1(*S*2). The market-clearing price is 93. As in the OCM auction, the selected sellers receive their individual start-up fees and the uniform market-clearing price for the supplied electricity. Both the total procurement cost and the total generation cost are equal to 192 (=93×2+6). The market price for buyers is 96 (=93+6÷2). This contract allocation is not production efficient, since *S*3's plant with relatively lower average total cost is idle.

Both the OCM and the PCM auctions are designed to sell the maximum amount of electricity where buyers' marginal willingness to pay is higher or equal to the average procurement cost. Tied offer combinations in the OCM auction are chosen in a way that generates lower procurement cost. Tied offer combinations in the PCM auction are selected by giving priority to those sellers whose offered cost is lower. Such a tie breaking mechanism gives the best performance chances to both complex-offer auctions, though to achieve similar tie breaking in real life applications would require additional costly computational power and time.

The Simple-Offer Auction

Notice that there is no difference between the OCM and the PCM auctions when the start-up fees are constrained to be zero. Minimizing offer cost or payment cost produces exactly the same contract allocation. Thus, either the OCM or the PCM algorithm could be used for the SOA by simply constraining all start-up fees to be zero. In the discussed example, an ISO considers two options: 1) buying 2 units from either *S*1 or *S*2, OR 2) buying 1 unit from *S*3 and 1 unit from *S*1(*S*2):

$$\text{Min}\{Price_{1,2}\times 2\ ,\ Price_{3}+Price_{1,2}\},$$

$$\text{Min}\{96\times 2,\ 90+96\}=90+96=186.$$

The auction chooses to buy 1 unit from *S*3 and 1 unit from *S*1(*S*2). The market-clearing price is 96. The selected sellers receive the uniform market-clearing price for the supplied electricity. The total procurement cost of electricity is equal to 192 (=96×2). This contract allocation is production efficient, since there is no way to generate 2 units of electricity cheaper than the chosen suppliers do. However, this outcome is problematic because *S*1(*S*2) is not able to recover all production costs and incurs a loss of -3 (=96-93-6). Since this outcome can not be sustained in the long run, *S*1(*S*2) would be forced to increase the offer in order to recover the fixed cost even when she sells only 1 unit of energy. The minimum sustainable offer is 99 dollars per unit. In this case, the outcome is:

Min{99×2, 90+99}=90+96=189.

The auction chooses to buy 1 unit from *S*3 and 1 unit from *S*1(*S*2). The market price for both buyers and sellers is 99. The total procurement cost of electricity is equal to 198 (=99×2). The contract allocation is production efficient.

In the presented example, given the assumption of truthful production cost revelation, the PCM auction produces the lowest procurement cost of electricity. It slightly outperforms the SOA and more significantly the OCM auction. On the other hand, the PCM auction is the only one to yield a production inefficient allocation. Notice that in the case of perfectly inelastic demand, production efficiency is equivalent to allocative efficiency. In the complex-offer auctions, the suppliers are able to reveal their costs and be reimbursed in a way that the costs are incurred. In the SOA, the sellers have to think how to recover the fixed costs through the offered prices. The SOA example shows that the sellers might face a risk of short-term losses.

Baltaduonis (2007) shows that the assumption of truthful production cost revelation cannot be reasonable in the complex-offer auctions. Due to the complex strategic behavior, both the OCM and the PCM auctions result in equally inefficient and costly outcomes. This paper investigates whether a SOA can curtail the anti-competitive behavior that is present in the COAs. A higher risk of losses in the SOA is a concern and is addressed in this paper as well.

2.2. Experimental Environment

Concerns about market power in the electric power industry abound. In the experiment, I develop a market environment that strictly controls for structural features of market power. Given the inelastic nature of the market demand for electricity, one might want to know which trading rules are more effective in suppressing the exercise of market power. Baltaduonis (2007) reports that both the OCM and the PCM auctions produce anti-competitive outcomes, even in the treatments with no market power. Since the SOA reduces the scope of possible strategic behavior, I hypothesize that the SOA should increase competitiveness in the market. This paper reports the findings related to the SOA performance in the same environment as described by Baltaduonis (2007).

In the context of capacity-constrained competitors, Holt (1989) defines market power as the ability to deviate *profitably* and *unilaterally* from the competitive outcome. Baltaduonis (2007) demonstrates that in the COAs, the offer complexity and the cyclical nature of the market demand for electricity create incentives to start-up plants during the higher demand periods. Consequently, the incentives to compete for baseload or shoulder demand units vanish even with the presence of cheap excess generation capacity. In fact, given the offer complexity and the cyclical nature of demand, it becomes impossible to design an environment with no market power, as defined by Holt, during the lower demand periods. However, opting for a SOA should eliminate these anticompetitive incentives while keeping the market supply unchanged. The theoretical reasoning follows the description of the designed environment.

Tables 1 and 2, as well as Figure 1 depict aggregate supply and demand in the experimental environment. Following RSW, I assume that the buyers perfectly reveal their willingness to pay. The second and third steps of the demand in Table 1 represent interruptible units of demand, whereas the units on the first step at 250 are the "must serve" units. The level of "must serve" demand varied among three levels: 1 unit in off-peak periods, 4 units during shoulder periods, and 14 units during peak periods.

2.2.1. Supply & Demand

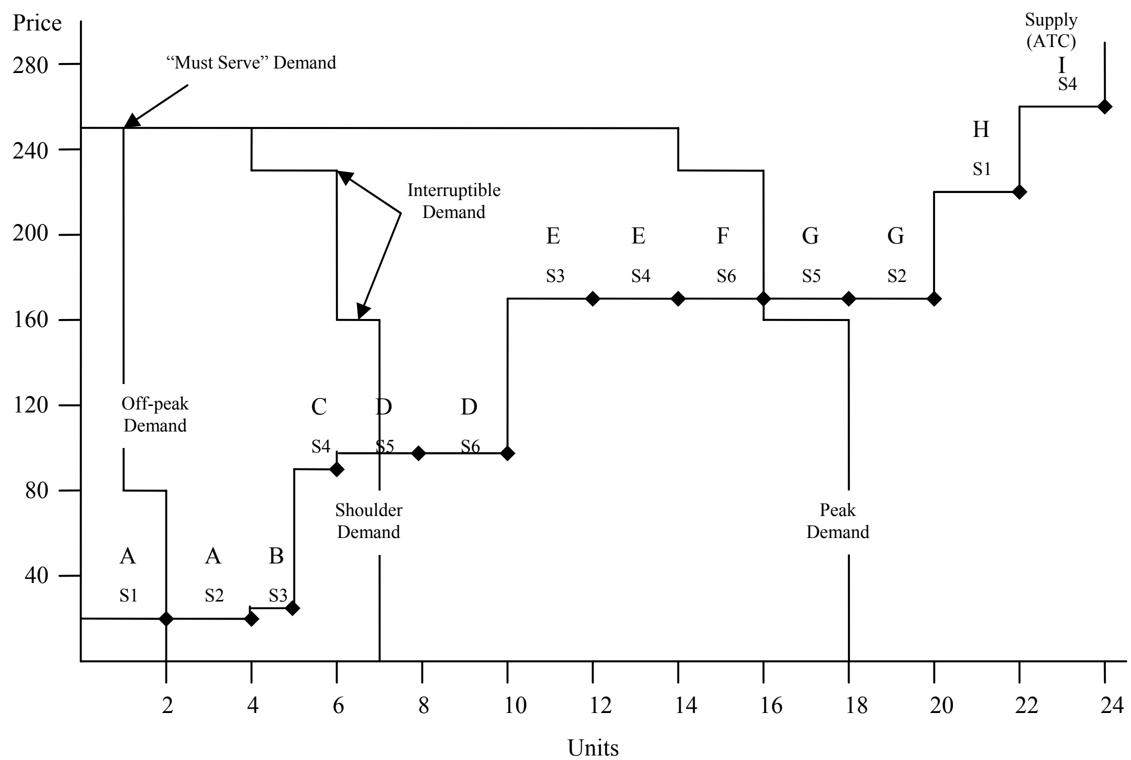

Figure 1. Market Structure and Design

Table 1. Demand Schedules

Demand	Quantity (demand values)		
	Step 1	Step 2	Step 3
Off-peak	1 (250)	1 (80)	N/A
Shoulder	4 (250)	2 (230)	1 (160)
Peak	14 (250)	2 (230)	2 (160)

In the designed market, there are thirteen plants of nine types. The technical characteristics of each plant are presented in Table 2. Some of them have low start-up costs with high production costs per unit, while other plants have high start-up costs but lower production costs. In the *No Power* treatment reported in this paper, all plants are owned by six firms (or sellers) denoted by an "*S*" and an identification number. *S*1 and *S*2 own two low cost (Type *A*) generation plants and two high cost generation plants (Type *H* and *G* respectively). *S*3 and *S*4 own two high cost (Type *E*) plants and, respectively, one baseload (Type *B*) generation plant and one intermediate cost (Type *C*) plant where generation capacity is one unit. *S*4 also owns a very high cost (Type *I*) peak capacity plant with average total cost exceeding even the resale value at the "must serve" level. Each *S*5 and *S*6 own one intermediate cost (Type *D*) plant and one high cost (Type *G* and *F* respectively) peak capacity generation plant.

Table 2. Minimum Average Total Costs (ATC) of Generation by Generator Type

Generator Type (Quantity)	Min Load Units	Max Load Units	Start-up Cost $	Energy Cost $/Unit	ATC at Max Load $/Unit	Total Load Units
A (2)	0	2	0	20	20	4
B (1)	1	1	10	15	25	1
C (1)	0	1	20	70	90	1
D (2)	0	2	6	93	96	4
E (2)	0	2	120	112	172	4
F (1)	0	2	80	132	172	2
G (2)	0	2	40	152	172	4
H (1)	0	2	0	225	225	2
I (1)	0	2	0	255	255	2
					Total	24

2.2.2. Unilateral Market Power

The pairs of sellers are designed to be Bertrand-like competitors that share an identical structure of generation costs at the certain demand level. In off-peak periods, the baseload plants owned by *S*1, *S*2 and *S*3 depict the market structure with three competitors described by Knoblauch (2005) and later analyzed by Baltaduonis (2006). During shoulder periods, the intermediate cost plants owned by *S*4, *S*5 and *S*6 resemble a similar market but with different cost distribution. When the start-up fee bidding is limited, Knoblauch shows that a Bertrand competition game in these markets results in a competitive outcome. Baltaduonis (2007) demonstrates that this result vanishes when the bidding on start-up fees is unregulated and the market demand is cyclical. However, I argue below that the competitive outcome does correspond to a pure-strategy Nash equilibrium in the SOA. The market during the peak periods is also designed to be competitive. Five sellers with ten units of similar cost capacity are competing to supply at least six units of peak demand.

SOA

In the electric power experiment, a firm is able to exert market power in a sealed bid-offer market if, for a given distribution of ownership of capacity, a firm profitably and unilaterally can submit an offer schedule above its costs (or equivalently withdraw some generating capacity) such that the market price rises above the competitive level. In the SOA treatment, the costs for the marginal units and therefore, the competitive market prices in the off-peak, shoulder 1, peak and shoulder 2 periods are respectively 20, 99, 172 and 93. In the SOA, there is no benefit to withhold capacity for later periods of a day.

Figure 1 and Table 2 show that there are at least two sellers who could supply the marginal units at the competitive market price during each period of a day. Such environment corresponds to a standard Bertrand competition game and is free of market power. Therefore, the market prices of 20, 99, 172 and 93 during the successive quarters of a day correspond to a pure strategy Nash equilibrium.

COA

In the COA treatments, at a given period of the demand cycle, the designed marginal generators have incentives to submit offers that are equal to the actual production costs of the marginal units. However, the asked fees do not necessarily need to be the actual start-up costs, as long as the asked seller prices are adjusted accordingly. Consider the OCM auction for an illustration.

Take the shoulder demand period following the off-peak. Each *S*5 and *S*6 owns a marginal intermediate cost plant that competes to supply the marginal seventh unit to the market. Either plant can generate this marginal unit at a cost of 99 [6+93]. If a seller offers to supply the unit at a cost higher than 99, the other seller would be able to undercut the offer by either lowering the fixed fee or the offered price. Therefore, a competitive price that all sellers receive should not exceed 99 during the shoulder periods. On the other hand, the price that all buyers pay in this case can be as high as 155. This would happen if other low cost generators (Type *A*, *B* and *C*) decided to recover their costs exclusively through fixed fees, i.e. submitting offers with prices equal to zero and start-up fees equal to 98 (<99) for one-unit capacity generators and equal to 196 (=2×98) for two-unit capacity generators. The OCM auction would select these offers before the marginal offers of 99. As discussed above, the amount of fees would be used to mark-up the buyer price during the shoulder period [99 + (98 × 4 ÷ 7) = 155]. In this case, the buyer price of 155 would correspond to a competitive outcome in a COA.

If we apply a similar analysis to other periods of the demand cycle, we get that the price (both for sellers and buyers) should not exceed 20 during the off-peak periods. The maximum price during the peak periods should be 172 and 230 for sellers and buyers respectively. And the price (both for sellers and buyers) should not exceed 93 during the shoulder periods following the peak demand. Notice that the shoulder periods before and after the peak demand have the same demand and supply structures. However, most of the plants are not idle after the peak period. Therefore, they do not incur start-up costs and do not receive start-up fees to continue generation during the second shoulder period of a day. For this reason, the competition during this period can be modeled as a standard Bertrand-competition game, where the competitive price equals the marginal cost.

This analysis, however, disregards the incentives to withhold the plants during the lower demand periods because of the opportunities to extract bigger start-up fees during the higher demand periods. Notice that the additional generation capacity would not improve competitiveness in this environment, because the suppliers of the additional capacity would have the same incentives to delay the start-ups. A competitive outcome becomes hardly possible. By allowing the sellers to submit complex-offers, the form of the auction automatically creates market power. This result holds for both the OCM and the PCM auctions.

The strategically rich environment of the COAs suggests that the sellers should be able to extract more social surplus by taking advantage of the offer complexity. A stirring strategic behavior might cause frequent allocative inefficiencies. After observing quite unsatisfactory performance of the OCM and the PCM auctions in a laboratory, the value-added of the complex auctions became questionable. As a result, I decided to run an SOA treatment and to compare the performance of complex- and simple-offer auctions, holding the production capabilities and demand levels constant.

3. Experimental Design and Procedures

To compare how the behavior and market performance differ in the complex- and simple-offer auctions, I conducted 12 market experiments using undergraduate students at George Mason University. Four sessions in each of the three treatments – OCM, PCM and SOA - were conducted using the experimental software that we developed at the Interdisciplinary Center for Economic Science at George Mason University. Each session lasted 53 trading days. The dataset discussed in this paper includes a total of 636 trading days. Each session lasted approximately 90 minutes.

The subjects in each market were provided with complete information on the market supply structure; i.e. every plant's minimum and maximum production capacity, start-up cost, cost per unit and the ownership of all plants were public information. Information on demand, however, was not available to the subjects. The situation was framed as a market for identical product to avoid the use of possibly intimidating or confusing electric power generation jargon. An experimenter informed the subjects that the costs and production capacities for each seller would not change during the experiment, but that the quantities of the product that the computer buyer will purchase would vary over the course of a day. In particular, the instructions indicated that the computer will purchase "low" amounts of product for the first quarter of a day, "medium" amounts for the second quarter of a day, "high" amounts for the third quarter of a day and "medium" amounts for the fourth quarter of a day. Each day consisted of a four period cycle: off-peak, shoulder 1, peak and shoulder 2 periods. The subjects did not know the total number of trading days in advance.

A subject had 75 seconds to submit an offer for each day.[4] An offer indicated the prices, start-up fees and quantities of the product that a seller was willing to supply from a particular plant over the course of the following day. The subjects could not alter the minimum and maximum quantities of the offer.[5] These quantities were set equal to the minimum and maximum capacities of a plant. However, the subjects could still effectively withdraw the capacity from the market by asking extremely high prices for those capacity units. Thus, in a COA, a seller had to decide on the price and the start-up fee for each plant and for each quarter of the upcoming day.[6] In the SOA, a seller had to decide only on the price for each plant and for each quarter of the upcoming day, as all start-up fees were set equal to zero. The instructions pointed out that the actual market price may be higher than their offered price and that all sellers would receive the same market price if their offers were selected. The sellers received start-up fees only for the periods when their plant had to be started. In the beginning of each day all plants were

[4] An exception was made for the first day offers. The sellers could take as much time as they needed to formalize their initial offers. Once the last seller submitted his/her offer for the first day, the following trading days were limited to 75 seconds. The chosen time frame is similar to one-minute trading days of the RSW electric power experiments.
[5] ISOs usually demand an explanation if generators change their offered generation capacity or technical constraints. Thus strategic behavior is somewhat limited with regards to these parameters of an offer.
[6] I am aware that there are various initiatives to regulate start-up cost reimbursement (e.g. limiting the ability to change the start-up fees freely; and partial start-up cost reimbursement) for electric power generators in real life. However, the purpose of the study is to investigate the performance of the two auctions when such regulations are absent.

idle. An experimenter also explained a rule of offer selection. A subject could, at any time within the 75-second period, revise her offer.

At the end of the trading day, all offers were sent to the computerized market coordinator. A market-clearing algorithm was applied and the results of a sealed-offer auction were sent back to the sellers. Each seller could see how many units she sold, what the market price for each period was and what profit/loss she earned on every owned capacity unit during each period of a day. The screens also displayed a history of the market prices from the past 10 days and the sold quantities during each quarter of the last day. The amount of paid fees was not public information.[7]

Subjects were paid $7 for showing up on time for the sessions. In addition to this show-up payment, the average earnings per subject for the data reported here was $21.55.

4. Results

On average, the SOA, OCM and PCM auctions extract 93, 92 and 94 percent, respectively, of maximum social surplus. All three auctions, on average, sell 32 units a day. Thus, considering that the demand side of the market is perfectly revealed in the experiment, lower levels of allocative efficiency must be attributed to higher degrees of production inefficiency. To have an idea how the captured social surplus is allocated among buyers and sellers, and how volatile the allocation is, Figure 2 depicts the buyer prices in each session of the three conducted *No Power* treatments. The last seventeen days of the data are grouped by level of demand (quarter) and then sequenced by how the demand varied over a market day: off-peak, shoulder 1, peak and shoulder 2.

[7] See Appendix A for the experimental instructions and Appendix B for an example of a subject screen during an experiment.

I evaluate the results with respect to the true cost revelation. The outcome of true cost revelation is particularly interesting in electricity markets because the design and the engineering of these complicated market systems often start with the assumption of true cost revelation. In Figure 2, the outcome of perfectly revealed costs is shown as a solid line. The dotted line represents the value of the nearest unit of interruptible demand. The prices up to the dotted line are 100% efficient with respect to allocation. As an attempt to control for the convergence of the bidding behavior, I focus on the last 17 market days (1/3 of all days) in each session.

From Figure 2, it is evident that the SOA is more likely to approach the true cost revelation outcome than either of the two COAs. Except for of shoulder 2 periods, both the OCM and the PCM auctions tend to significantly deviate from the outcome of perfectly revealed costs. In the SOA, the buyer prices substantially depart from the competitive outcome only during the peak periods. Notice that in shoulder 2 periods, most of the plants are already operating and, therefore, are not eligible for the start-up fees. Thus, at the end of a day the sellers compete purely on prices in all three auctions. The absence of fixed costs leads to relatively competitive outcomes during shoulder 2 periods across all auctions. The conformity is not accidental, since all three offer selection rules are identical in the absence of fixed fees.

In what follows, the experimental results are summarized as a series of five findings. In addition to the qualitative results displayed in the figures, I analyze the data using a mixed-effects model for repeated measures on each of several sessions using different subjects.[8] The results from estimating this model for the buyer prices by level of demand are given in Table 3. The dependent variable in this case is the difference

[8] See e.g. Longford 1993.

between the observed buyer price (*Price*) and the buyer price from the OCM auction when generation costs are perfectly revealed by the sellers, P^t. In the regressions, the OCM auction is used as a benchmark institution to represent the status quo. The treatment effects (*PCM* and *SOA*) are modeled as (zero-one) fixed effects, whereas the sessions are modeled as random effects, e_i. As mentioned above, the experimental days are divided into three equal groups to capture effects like learning over time. In the model, the data from the *First* and *Second* groups (days 1-18 and 19-36 respectively) are identified by (zero-one) dummy variables. Specifically, the estimated model is:

$$Price_{ij}-P^t=\mu+e_i+\beta_1 PCM_i+\beta_2 SOA_i+\beta_3 First_i+\beta_4 Second_i+\beta_5 PCM_i\times First_i+$$
$$\beta_6 PCM_i\times Second_i+\beta_7 SOA_i\times First_i+\beta_8 SOA_i\times Second_i+\varepsilon_{ij},$$

where the sessions are indexed by i=1,…,12 and the repeated market days by j=1,…,53.[9] $e_i \sim N(0,\sigma^2{}_1)$ and $\varepsilon_{ij} \sim N(0,\sigma^2{}_{2,i})$. I begin with the findings related to the procurement cost and then follow with the results regarding the efficiency of the auctions.

Finding 1: *Ceteris paribus, changing the auction institution from a COA to a SOA significantly reduces buyer prices in the periods when start-up costs are relevant (off-peak, shoulder 1 and peak periods). Buyer prices are similar in shoulder 2 periods of all auctions, as no new plants need to be started and, therefore, the start-up fees are absent.*

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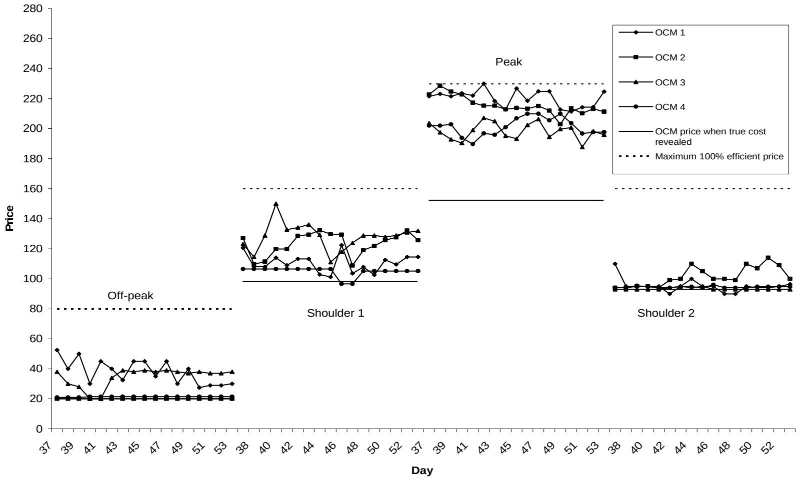
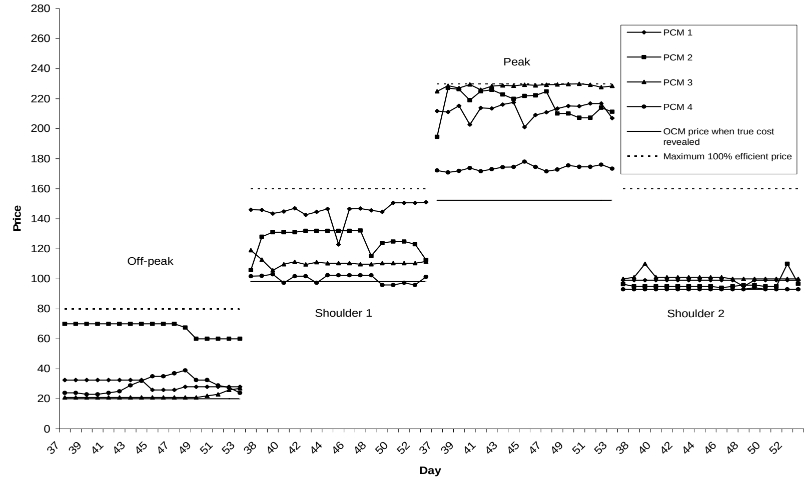
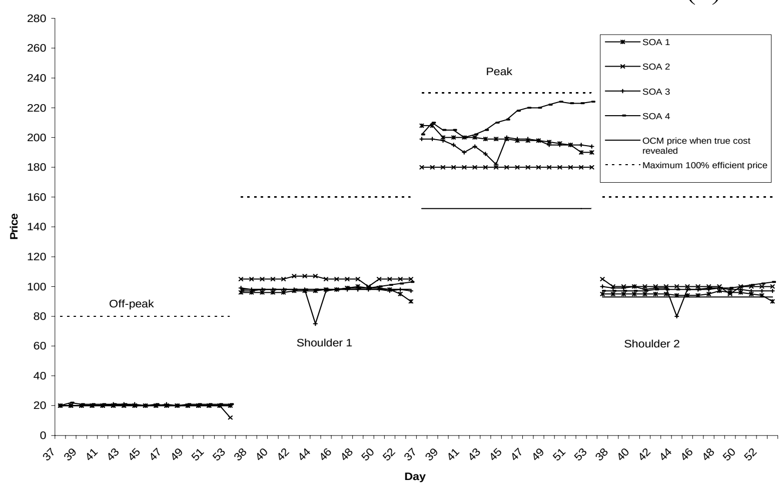
[9] Similar mixed-effects models were used in other experimental studies of electricity markets (Rassenti, Smith and Wilson, 2003a and 2003b; Kiesling and Wilson, 2007).



(a) OCM/No Power



(b) PCM/No Power



(a) SOA/No Power

Figure 2. Buyer Prices by Level of Demand for the Last 17 Market Days in Each Session

Table 3. Estimates of the Linear Mixed Effects Model of Treatment Effects for the Buyer Prices

$Price_{ij} - P^t = \mu + e_i + \beta_1 PCM_i + \beta_2 SOA_i + \beta_3 First_i + \beta_4 Second_i + \beta_5 PCM_i \times First_i + \beta_6 PCM_i \times Second_i + \beta_7 SOA_i \times First_i + \beta_8 SOA_i \times Second_i + \varepsilon_{ij},\ e_i \sim N(0,\sigma^2_1)$ and $\varepsilon_{ij} \sim N(0,\sigma^2_{2,i})$						
	Estimate	Std. Error	Degrees of Freedom	H_a	t-statistic	p-value
Off-peak						
μ	**7.37**	**5.48**	**618**	**$\mu>0$**	**1.35**	**0.1787**
PCM	**9.64**	**7.73**	**9**	**$\beta_1\neq0$**	**1.25**	**0.2438**
SOA	**-8.58**	**7.70**	**9**	**$\beta_2\neq0$**	**-1.12**	**0.2935**
First	-6.72	1.22	618	$\beta_3\neq0$	-5.51	<.0001
Second	-2.72	1.22	618	$\beta_4\neq0$	-2.23	0.0262
PCM×First	4.25	1.46	618	$\beta_5\neq0$	2.92	0.0037
PCM×Second	1.04	1.46	618	$\beta_6\neq0$	0.71	0.4749
SOA×First	5.06	1.28	618	$\beta_7\neq0$	3.95	0.0001
SOA×Second	2.35	1.28	618	$\beta_8\neq0$	1.84	0.0669
Shoulder 1						
μ	**18.40**	**4.09**	**618**	**$\mu>0$**	**4.50**	**<.0001**
PCM	**-2.17**	**5.66**	**9**	**$\beta_1\neq0$**	**-0.38**	**0.7105**
SOA	**-19.53**	**5.71**	**9**	**$\beta_2\neq0$**	**-3.42**	**0.0077**
First	-7.97	2.17	618	$\beta_3\neq0$	-3.67	0.0003
Second	-1.61	2.17	618	$\beta_4\neq0$	-0.74	0.4578
PCM×First	15.69	2.44	618	$\beta_5\neq0$	6.44	<.0001
PCM×Second	3.26	2.44	618	$\beta_6\neq0$	1.34	0.1809
SOA×First	-1.05	2.82	618	$\beta_7\neq0$	-0.37	0.7102
SOA×Second	3.57	2.82	618	$\beta_8\neq0$	1.27	0.2054
Peak						
μ	**57.17**	**5.95**	**618**	**$\mu>0$**	**9.61**	**<.0001**
PCM	**2.96**	**8.41**	**9**	**$\beta_1\neq0$**	**0.35**	**0.7327**
SOA	**-17.02**	**8.44**	**9**	**$\beta_2\neq0$**	**-2.02**	**0.0744**
First	-2.17	1.84	618	$\beta_3\neq0$	-1.18	0.2399
Second	4.35	1.84	618	$\beta_4\neq0$	2.36	0.0187
PCM×First	-6.45	2.50	618	$\beta_5\neq0$	-2.58	0.0100
PCM×Second	-7.71	2.50	618	$\beta_6\neq0$	-3.09	0.0021
SOA×First	11.42	2.59	618	$\beta_7\neq0$	4.41	<.0001
SOA×Second	-1.47	2.59	618	$\beta_8\neq0$	-0.57	0.5710
Shoulder 2						
μ	**0.83**	**0.93**	**618**	**$\mu>0$**	**0.90**	**0.3709**
PCM	**0.98**	**1.45**	**9**	**$\beta_1\neq0$**	**0.67**	**0.5169**
SOA	**2.29**	**1.50**	**9**	**$\beta_2\neq0$**	**1.53**	**0.1615**
First	-0.51	0.28	618	$\beta_3\neq0$	-1.80	0.0724
Second	-0.31	0.28	618	$\beta_4\neq0$	-1.10	0.2724
PCM×First	10.94	1.25	618	$\beta_5\neq0$	8.77	<.0001
PCM×Second	3.67	1.25	618	$\beta_6\neq0$	2.95	0.0033
SOA×First	0.07	1.16	618	$\beta_7\neq0$	0.06	0.9539
SOA×Second	2.61	1.16	618	$\beta_8\neq0$	2.25	0.0248

Note. The linear mixed-effects model is fit by maximum likelihood with 636 original observations and 12 sessions. For purposes of the brevity the session random effects are not included in the table.

Support: Figure 2 clearly illustrates that both the OCM and the PCM auctions can produce higher buyer prices than the SOA in all three periods where new plants need to be started, i.e. in off-peak, shoulder 1 and peak periods. Except for peak periods, buyer prices in the SOA settle very close to the Bertrand competitive equilibrium, i.e. 20, 99, 172 and 93, during the respective quarters of a day. SOA prices for peak periods do not come close to the expected competitive level of 172. My speculation is that the incentives to undercut the competitors' offers are weaker in the peak periods because winning a marginal contract and setting a lower uniform market price also means smaller profits for the low or/and intermediate cost plants that the seller owns. On the other hand, there is no discernible separation in shoulder 2 prices. Since most of the plants are operating during the peak periods, no new plants need to be started when market demand falls. The absence of start-up fees makes the three offer selection rules identical, which consequently should lead to similar outcomes.

These qualitative observations are supported by estimates from the mixed-effects model in Table 3. When the PCM treatment shows no significant impact on the buyer prices compared to the OCM auction, the SOA substantially reduces prices by 8.6 (*p-value*=0.2935), 19.5 (*p-value*=0.0077) and 17 (*p-value*=0.0744) experimental dollars in the off-peak, shoulder 1 and peak periods, respectively. The prices in shoulder 2 periods are not significantly different across all three auctions (*p-values*=0.5169, 0.1615 for PCM and SOA, respectively).■

With less room for strategic behavior, the SOA harnesses the market power that is present in the COAs and significantly raises the level of competition in the market. The second and third findings describe the performance of the three auctions with regards to allocative and production efficiency.

Finding 2: *Markets in the SOA treatment quickly stabilize at an allocative efficient quantity at all levels of demand, whereas the COAs continue to interrupt market demand throughout the experiment, especially during the peak periods.*

Support: On only eighteen occasions (out of possible 848 = 53 days × 4 quarters × 4 sessions) the SOA exchanged an allocative inefficient quantity of the product. Seventeen of these occasions happened during the peak periods. The latest inefficient allocation was observed during the 12th market day in session 2. The OCM (PCM) auction experienced 55 (24) allocative inefficient exchanges, with the latest observation being from the 44th (53rd) market day. 44 (19) or 80% (79%) of these inefficient exchanges happened during the peak periods. It is easy to see from Figure 2 that the last 17 days in all sessions resulted in 100% efficient buyer prices. However, this does not necessarily mean that all OCM sessions supplied the efficient quantity to the market during all those days. In fact, the demand had to be interrupted on 5 occasions (out of possible 272 = 17 days × 4 quarters × 4 sessions), because the price for the efficient amount exceeded buyers' maximum willingness to pay. Similarly, the demand was interrupted on 4 occasions during the last 17 days in the PCM sessions.■

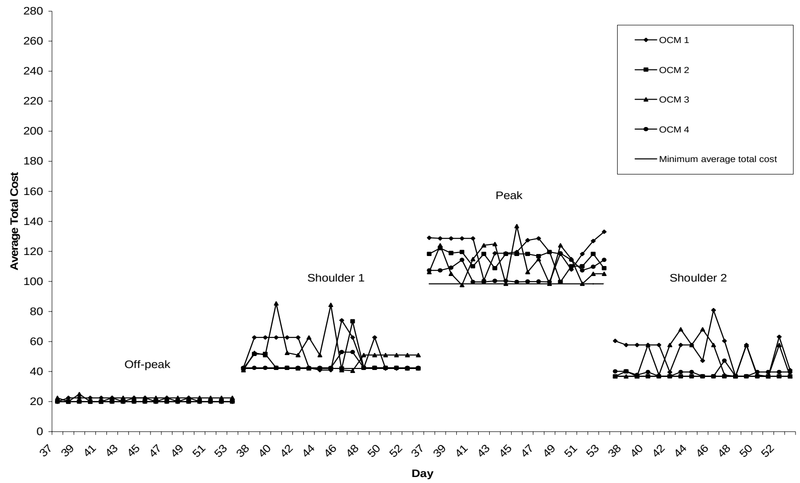
Failure to supply the efficient amount of product to the market is not the only source of possible inefficiencies. The social surplus might also be reduced by production inefficiencies, i.e. the situations when the higher cost plants produce the product instead of the lower cost plants.

Finding 3: *Except during peak periods, all treatments exhibit similar degrees of production inefficiency. In peak periods, the PCM auction achieves higher production efficiency than either the SOA or the OCM auction.*

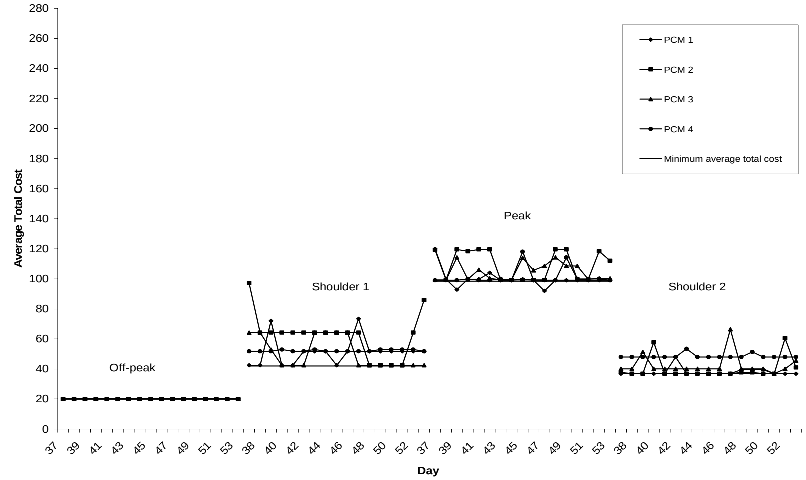
Support: Figure 3 and the estimates from the mixed-effects model in Table 4 report evidence that in all but peak periods, the three treatments are not significantly different from each other. The dependent variable in this case is the difference between the observed production cost (*ProdCost*) and the minimum production cost for the exchanged quantity, $ProdCost^*$.[10] Considering the last 17 days in all sessions, the treatment effects are insignificant for off-peak, shoulder 1 and shoulder 2 periods.

In peak periods, the SOA treatment raises production costs above the PCM level by 83.3 experimental dollars (*p-value*=0.0298). The SOA treatment lowers production costs below the OCM level by 57.3 experimental dollars, but the difference is not statistically significant (*p-value*=0.1180). High production inefficiencies in the OCM auction stem from frequent occasions when the very high cost generators of H and I types are called to produce. The owners of the most inefficient plants (type H and I) are able to win contracts and profitably supply to the market by offering low prices and recovering their variable costs through high start-up fees. During the last 17 days of the OCM sessions, these plants are selected and make positive profits during 42 days [out of possible 68 = 17days× 4sessions]. The same plants sell profitably on 6 days in the PCM sessions and never in the SOA sessions.■

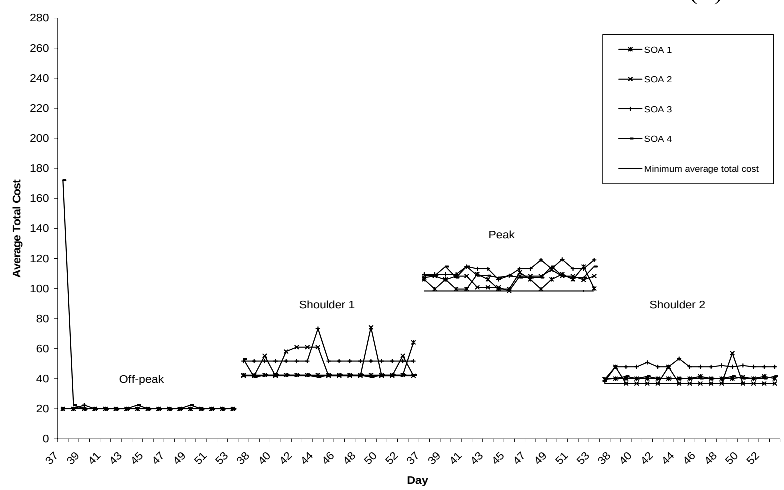
[10] An interpretation of the regression results might be problematic if the exchanged quantity fluctuates across the days. However, this problem does not arise here since during the last 17 days of the experiment, the demand had to be interrupted only on 5 occasions (out of possible 272 = 17 days × 4 quarters × 4 sessions) in the OCM treatment, and on 4 occasions in the PCM treatment.



(a) OCM/No Power



(b) PCM/No Power



(a) SOA/No Power

Figure 3. Average Total Costs by Level of Demand for the Last 17 Market Days in Each Session

Table 4. Estimates of the Linear Mixed Effects Model of Treatment Effects for the Production Costs

$$ProdCost_{ij} - ProdCost^{*} = \mu + e_i + \beta_1 PCM_i + \beta_2 SOA_i + \beta_3 First_i + \beta_4 Second_i + \beta_5 PCM_i \times First_i + \beta_6 PCM_i \times Second_i + \beta_7 SOA_i \times First_i + \beta_8 SOA_i \times Second_i + \varepsilon_{ij},\ \ e_i \sim N(0,\sigma^2_{1}) \text{ and } \varepsilon_{ij} \sim N(0,\sigma^2_{2,i})$$

	Estimate	Std. Error	Degrees of Freedom	H_a	t-statistic	p-value
Off-peak						
Due to the lack of variability of the dependent variable, the model cannot be estimated for the off-peak periods. Treatment averages and standard deviations are presented instead.						
	Average	Std. Dev.				
OCM	**1.69**	**2.38**				
PCM	**0.00**	**0.00**				
SOA	**4.76**	**36.85**				
Shoulder 1						
μ	**37.02**	**17.61**	**618**	**$\mu>0$**	**2.10**	**0.0359**
PCM	**42.37**	**24.90**	**9**	**$\beta_1\neq0$**	**1.70**	**0.1230**
SOA	**10.94**	**24.92**	**9**	**$\beta_2\neq0$**	**0.44**	**0.6711**
First	113.99	15.01	618	$\beta_3\neq0$	7.60	<.0001
Second	36.72	15.01	618	$\beta_4\neq0$	2.45	0.0147
PCM×First	-58.36	20.88	618	$\beta_5\neq0$	-2.79	0.0054
PCM×Second	-12.55	20.88	618	$\beta_6\neq0$	-0.60	0.5481
SOA×First	6.28	21.04	618	$\beta_7\neq0$	0.30	0.7653
SOA×Second	-31.00	21.04	618	$\beta_8\neq0$	-1.47	0.1412
Peak						
μ	**222.86**	**25.18**	**618**	**$\mu>0$**	**8.85**	**<.0001**
PCM	**-140.65**	**34.81**	**9**	**$\beta_1\neq0$**	**-4.04**	**0.0029**
SOA	**-57.34**	**33.18**	**9**	**$\beta_2\neq0$**	**-1.73**	**0.1180**
First	-65.92	23.85	618	$\beta_3\neq0$	-2.76	0.0059
Second	-50.64	23.85	618	$\beta_4\neq0$	-2.12	0.0341
PCM×First	120.20	32.70	618	$\beta_5\neq0$	3.68	0.0003
PCM×Second	97.20	32.70	618	$\beta_6\neq0$	2.97	0.0031
SOA×First	47.65	29.11	618	$\beta_7\neq0$	1.64	0.1022
SOA×Second	35.60	29.11	618	$\beta_8\neq0$	1.22	0.2218
Shoulder 2						
μ	**45.13**	**19.22**	**618**	**$\mu>0$**	**2.35**	**0.0192**
PCM	**-3.62**	**26.87**	**9**	**$\beta_1\neq0$**	**-0.13**	**0.8958**
SOA	**13.81**	**26.98**	**9**	**$\beta_2\neq0$**	**0.51**	**0.6208**
First	116.79	12.20	618	$\beta_3\neq0$	9.58	<.0001
Second	28.77	12.20	618	$\beta_4\neq0$	2.36	0.0187
PCM×First	-55.59	17.20	618	$\beta_5\neq0$	-3.23	0.0013
PCM×Second	-14.69	17.20	618	$\beta_6\neq0$	-0.85	0.3935
SOA×First	-51.16	16.11	618	$\beta_7\neq0$	-3.18	0.0016
SOA×Second	-21.09	16.11	618	$\beta_8\neq0$	-1.31	0.1912

Note. The linear mixed-effects model is fit by maximum likelihood with 636 original observations and 12 sessions. For purposes of the brevity the session random effects are not included in the table.

Next I consider another criterion to compare the performance of three auction mechanisms – price volatility. Inflated and volatile wholesale electricity prices have been a concern since the deregulation of electricity markets.

Finding 4: *The variance of buyer prices from day to day for the same level of demand is lower with the SOA than with the OCM auction for all levels of demand.*

Support: Figure 2 presents the dynamics of buyer prices in the auctions. Figure 4 summarizes the price variances for the twelve sessions presented here. The statistics use the last 17 days of each session to allow for the convergence of the observed prices evident in Table 3. Individual session variances are averaged across each treatment. From Figure 4, it is clear that the SOA reduces the volatility of prices compared to the OCM auction in all periods. Lower price volatility in the SOA compared to the PCM auction is clear only in the off-peak and shoulder 1 periods.■

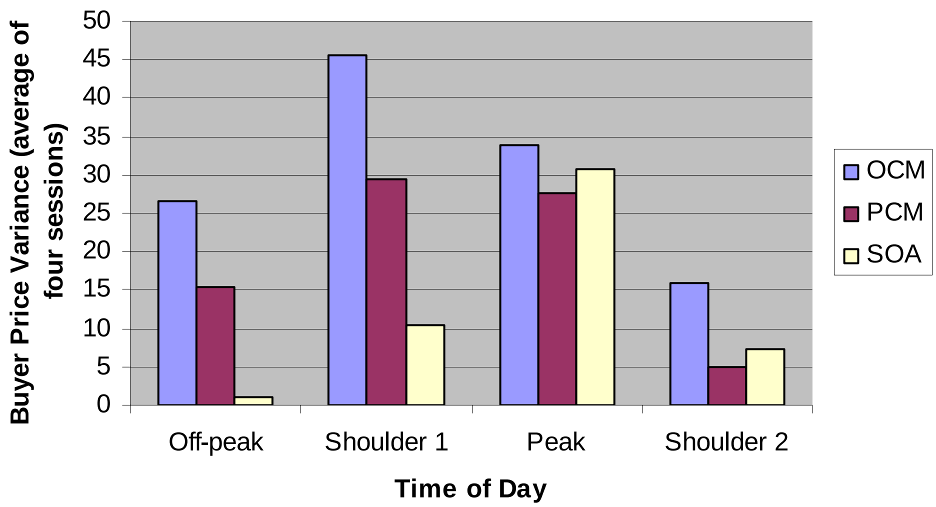


Figure 4. Buyer Price Variances by Treatment for the Last 17 Market Days

According to the above findings the SOA outperforms the OCM auction with respect to allocative efficiency, electricity cost to consumers and price volatility. The SOA improves over the PCM outcomes with respect to most of these criteria as well. On the other hand, in the beginning of this paper, the concern was raised that the sellers might face a higher risk of short-term losses in the SOA. Finding 5 addresses this issue.

Finding 5: *Markets in the SOA treatment accumulate more short-term losses than in the COA treatments; however, the relative size of the losses is small.*

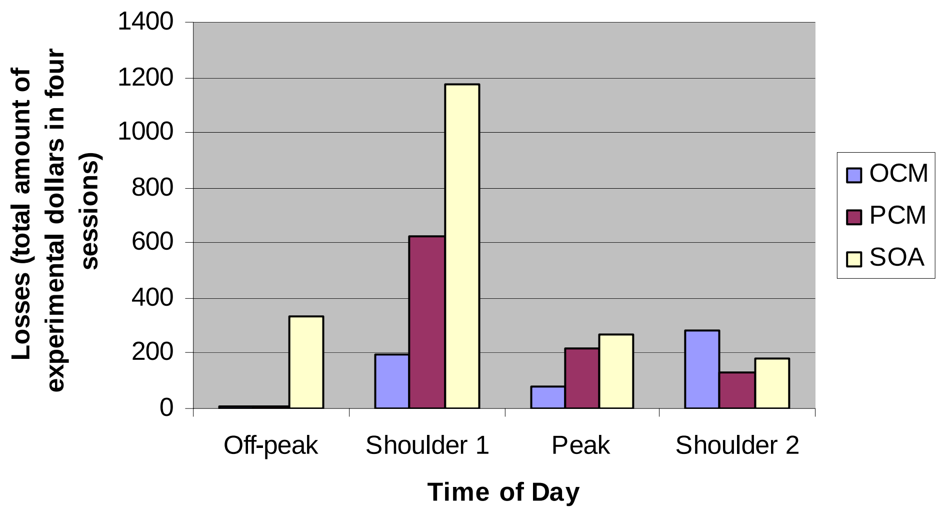


Figure 5. Total Losses by Treatment for the Last 17 Market Days

Support: The total amounts of experienced losses in the OCM, PCM and SOA sessions are 24346, 11679 and 38192 experimental dollars, respectively. The losses substantially decline towards the end of the sessions. The amounts of losses during the last 17 days of the experiment are 562, 973 and 1966 experimental dollars respectively. Compared to the earnings during these days, the losses represent 0.3%, 0.6% and 1.3% of market profits. Figure 5 summarizes the total amounts of experienced losses by quarter of the day. It is clear from Figure 5 that the SOA results in more short-term losses than do the COAs. ■

5. Conclusions

In the dynamic trading environment that models wholesale electricity markets, the SOA reduces prices to consumers, lowers price volatility and achieves allocative efficiency more quickly than either of the two COAs. These gains are achieved at the cost of higher risk of short term losses. The losses, however, are rather small in the described environment. The SOA prices converge to the competitive levels, while the COAs' prices approach the levels observed in an environment with structural market power. There is less room for strategic behavior in the SOA. Consequently, the SOA is able to mitigate anti-competitive effects that are present in the COAs, such as the incentive to withhold the lower cost generation capacity for the higher demand periods and the ability to sell higher cost units by manipulating the combination of offered fees and prices. The outcomes for shoulder 2 periods, on the other hand, are competitive and predictable across all three auctions. Since the start-up costs are basically absent in the shoulder 2 periods, one might imagine how simpler and more transparent these markets could be if fixed costs did not exist. But they do. And it is clear that allowing the sellers to recover their fixed and variable costs separately does not enhance the transparency in the market.

For policy makers the lesson is clear: keep market institutions simple. Allowing market participants to reveal more information and trying to make use of that information also creates more opportunities to act strategically. If there is a way to strike it rich, the market participants find it.

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Appendix A: Experimental Instructions

<page 1>

Welcome

This is an experiment in the economics of decision-making. If you read the instructions carefully and make good decisions, you may earn a considerable amount of money that will be paid to you in CASH at the end of the experiment.

The experiment will take place through the computer terminals at which you are seated. If you have any questions at any time, please raise your hand and a monitor will come to assist you.

In this experiment, owners of plants sell an identical product to a computer buyer every day. Each day lasts 75 seconds. You are an **owner** of #yourNumberOfPlants# plants. There are #numberOfSellers# sellers and #numberOfPlants# plants including yours. Each seller owns between 1 and 4 plants.

<page 2>

Each day is divided into 4 quarters. Each quarter is represented by a line in the table at the top of your screen. The computer will purchase varying quantities of the product over the course of a day: Low, Medium, High and Medium amounts.

Sellers submit offers to sell. An offer indicates the prices and quantities of the product that you are willing to sell during the course of the following day. All quantities are measured in number of units.

<page 3 OCM and PCM>

You as a seller are able to decide:

Price/unit is the price per unit you are willing to sell at during that quarter from that plant. This is the minimum price at which you are willing to sell. The actual market price may be higher depending on the demand of the product. Each seller receives the same market price for sold units during the quarter. The market price is the highest accepted Price/unit among all of the sellers. If you sell the product you also incur a cost per unit sold. This cost is listed on the right side under the table and must be paid for each unit you sell.

Start-Up Fee is a fee that is paid to you for turning on your plant. The fee is paid to you only if the plant was not operating during the previous quarter. When your plant is turned on, you also must pay the start-up cost, which is listed on the right side under the table.

You will be able to make this decision for each quarter of the upcoming day for each plant that you have.

<page 3 SOA>

You as a seller are able to decide:

Price/unit is the price per unit you are willing to sell at during that quarter from that plant. This is the minimum price at which you are willing to sell. The actual market price may be higher depending on the demand of the product. Each seller receives the same market price for sold units during the quarter. The market price is the highest accepted Price/unit among all of the sellers. If you sell the product you also incur a cost per unit sold. This cost is listed on the right side under the table and must be paid for each unit you sell.

You will be able to make this decision for each quarter of the upcoming day for each plant that you have.

<page 4 OCM and PCM>
To switch between plants click on the tabs at the top of your screen. To enter the values select the appropriate cell in the table and double click.

Some offer values are automatically filled in for you:

Min Qty is the minimum number of units you are willing to sell during that quarter from that plant. Min Qty must be ≥ Minimum Capacity, which is specified under the table. This will be filled with that plant's Minimum Capacity.

Max Qty is the maximum number of units you are willing to sell during that quarter from that plant. Max Qty must be ≤ Maximum Capacity, which is specified under the table. Max Qty must also be ≥ Min Qty. This will be filled with that plant's Maximum Capacity.

<page 4 SOA>

To switch between plants click on the tabs at the top of your screen. To enter the values select the appropriate cell in the table and double click.

Some offer values are automatically filled in for you:

Min Qty is the minimum number of units you are willing to sell during that quarter from that plant. Min Qty must be ≥ Minimum Capacity, which is specified under the table. This will be filled with that plant's Minimum Capacity.

Max Qty is the maximum number of units you are willing to sell during that quarter from that plant. Max Qty must be ≤ Maximum Capacity, which is specified under the table. Max Qty must also be ≥ Min Qty. This will be filled with that plant's Maximum Capacity.

When your plant is turned on, you also must pay the start-up cost, which is listed on the right side under the table. You will not receive the **Start-Up Fee** for turning on your plant.

<page 5 PCM>

Offers are sent to the computerized market coordinator when you click the Submit button or when the day is over. Your offer from the previous day will be automatically submitted for you if you choose not to make any changes during the course of a day.

The computerized market coordinator accepts those offers that satisfy the market demand during the day at the *lowest total procurement cost*, simultaneously determining the market price as the highest accepted Price/unit for that quarter.

If your offer has not been accepted, it means that other offers were able to satisfy the market demand at a lower or equal cost. The results are displayed on the right side of the table; you may need to scroll to the right to see them. Once you have reviewed the results of the previous day enter your offers for the next day for each plant and submit.

The right side of the table is filled in after everyone has submitted their offers.

Your profit during each quarter of a day is:

(Units Sold × market price + Start-Up Fees collected) – (Units Sold × Cost/unit + Start-Up Costs incurred)

<page 5 OCM>

Offers are sent to the computerized market coordinator when you click the Submit button or when the day is over. Your offer from the previous day will be automatically submitted for you if you choose not to make any changes during the course of a day.

The computerized market coordinator accepts those offers that satisfy the market demand during the day at the *lowest total offered cost*. After the offers are selected, the market price is determined as the highest accepted Price/unit for that quarter.

If your offer has not been accepted, it means that other offers were able to satisfy the market demand at a lower or equal cost. The results are displayed on the right side of the table; you may need to scroll to the right to see them. Once you have reviewed the results of the previous day enter your offers for the next day for each plant and submit.

The right side of the table is filled in after everyone has submitted their offers.

Your profit during each quarter of a day is:

(Units Sold × market price + Start-Up Fees collected) – (Units Sold × Cost/unit + Start-Up Costs incurred)

<page 5 SOA>

Offers are sent to the computerized market coordinator when you click the Submit button or when the day is over. Your offer from the previous day will be automatically submitted for you if you choose not to make any changes during the course of a day.

The computerized market coordinator orders offered Prices/unit from lowest to highest for each quarter of the day. Market's bids to buy the product are ordered from highest to lowest. These two sorted lists will cross. The offered Price/unit where these lists cross becomes the market price during the quarter. The market coordinator accepts all offers with Prices/unit lower than the market price. If there is more than one offer exactly equal to the market price, then as many of those offers will be accepted as it is enough to satisfy the market demand during that quarter of the day.

If your offer has not been accepted, it means that other offers were able to satisfy the market demand at a lower or equal cost. The results are displayed on the right side of the table; you may need to scroll to the right to see them. Once you have reviewed the results of the previous day enter your offers for the next day for each plant and submit.

The right side of the table is filled in after everyone has submitted their offers.
Your profit during each quarter of a day is:
(Units Sold × market price) – (Units Sold × Cost/unit + Start-Up Costs incurred)

<page 6>
A history of the prices from the past 10 days and the sold quantities during each quarter of the last day are displayed in the bottom portion of your screen.

Information about all plants (including yours) is available to all sellers by clicking on the Technology and costs button.

Plants are restarted at the beginning of each day, meaning that during the first quarter of each day you receive your start-up fee and incur the start-up cost if you sell the product.

At the end of today's session, your 'computer dollars' will be converted into cash at a rate of #exchangeRate# computer dollars to US$1. If you have any questions please raise your hand. Press Start when you are ready to begin.

Even if you decide to keep your offer from the previous day, click the Submit button. The experiment will advance to the next day after everyone has clicked on the Submit button.

Appendix B: Sample Screen Shot

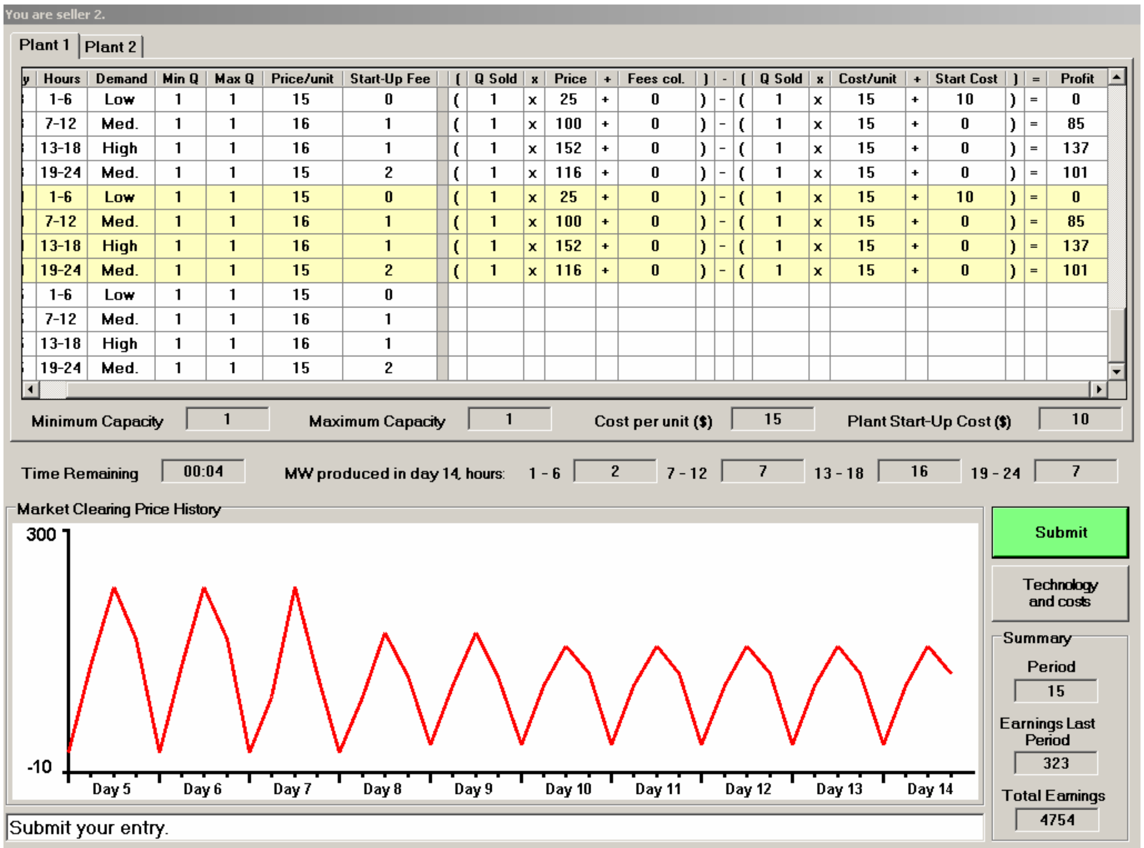

Figure B1. Sample Screen Shot.